

Capacity Planning and Energy Management Strategy of Residential Multi-microgrid System Considering Uncertainty

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Abstract- This study investigates the optimal capacity and performance of residential multi-microgrid systems (MMGs) integrating photovoltaic (PV), wind turbine (WT), and energy storage system (ESS) under uncertain solar irradiance and wind speed data. It utilizes an Iterative Pareto Fuzzy (IPF) technique for capacity optimization, balancing reliability, overall cost, and dump load size as objective functions, and incorporates an Energy Management Strategy (EMS) for operational efficiency. The IEEE 33-bus test system is modified into five autonomous microgrids for analysis. Optimization results reveal trade-offs between objectives: MG 3 boasts the highest reliability but incurs the highest overall cost, while MG 1 and MG 5 showcase more cost-effective designs. Robustness analysis conducted with Gaussian and Weibull noise models demonstrates the resilience of the proposed residential MMG design to data uncertainty with self-sufficiency index (SSI) exceeding 80 percent. This study provides valuable insights into designing and operating effective residential MMG for increased energy autonomy and resilience.

Keywords Residential multi-microgrid, capacity optimization, Iterative-Pareto-Fuzzy, energy management strategy, multi-objective function.

Nomenclature

Abbreviations

ESS	Energy storage system
GSO	Group search optimization
IPF	Iterative Pareto Fuzzy
MMG	Multi-microgrid
PDF	Probability density function
PSO	Particle swarm optimization
PV	Photovoltaic
RESs	Renewable energy sources
SSI	Self-sufficiency index
WT	Wind turbine

Symbols

α and b	WT output power parameters
α_{ESS} , α_{PV} , α_{WT}	Initial cost of ESS, PV, and WT
$\alpha_{OM_{ESS}}$	Annual OM cost of ESS

$\alpha_{OM_{PV}}$	Annual OM cost of PV
$\alpha_{OM_{WT}}$	Annual OM cost of WT
α_{SPV} , α_{SWT}	Salvage value of PV and WT
β	Average inflation rate
γ	Average interest rate
ν	Average escalation rate
η_{PV} , η_{WT}	Efficiency of PV and WT
G	Solar irradiance
ESS_{chg_dischg}	ESS hourly charging/discharging power
$ESS_{Limit_chg_dischg}$	ESS hourly charging/discharging limit
ESS_{SoC}	SoC of ESS
ESS_{minSoC}	Minimum SoC of ESS
ESS_{maxSoC}	Maximum SoC of ESS
$L_{bus\ demand}$	Load of bus in each microgrid
$L_{daily\ bus}$	Daily load profile of each microgrid
$L_{daily\ pattern}$	Daily residential load pattern

L_{max}	Maximum load of bus in each microgrid
L_{norm}	Normalization of load
L_h	Life span of the project
L_{ESS}, L_{PV}, L_{WT}	Life span of the ESS, PV and WT
N_{ESS}	Per unit rated power of ESS
N_{ESSmin}	Minimum power of ESS
N_{ESSmax}	Maximum power of ESS
N_{PV}	Per unit rated power of PV
N_{PVmin}	Minimum power of PV
N_{PVmax}	Maximum power of PV
N_{WT}	Per unit rated power of WT
N_{WTmin}	Minimum power of WT
N_{WTmax}	Maximum power of WT
$N\sim(\mu, \sigma)$	Normal PDF with scale and shape parameter
P_{demand}	Demand power
P_{gen}	Generated power
P_r	Rated power
$P_{PVout}(h)$	PV output power
$P_{WTout}(h)$	WT output power
V	Wind speed
V_{ci}, V_{co}, V_r	Cut-in, cut-out, and rated wind speed
$W\sim(c,k)$	Weibull PDF with scale and shape parameter

1. Introduction

The rapid growth of renewable energy sources (RESs), like solar and wind power, has revolutionized energy landscapes [1-3], yet their inherent variability poses challenges for ensuring reliable and sustainable electricity supply [4-6]. Hybrid multi-microgrid systems (MMGs) emerge as a promising solution [7], integrating diverse RESs with energy storage systems (ESSs) to operate autonomously and deliver reliable power to local communities [8,9].

Optimizing MMG design and operation remains a complex task, requiring a delicate balance between multiple objectives [10,11]: maximizing reliability, minimizing cost, and reducing energy losses through dump loads. Existing studies often prioritize a single objective which is cost minimization [12-15] or reliability maximization [16], neglecting the dynamic interplay between them. Additionally, accurate forecasting of solar irradiance and wind speed, crucial for efficient MMG operation, is often

hampered by uncertainties [17-19], further impacting system resilience.

Previous research has explored various optimization techniques for MMGs, focusing on individual objectives. References [20,21] used a particle swarm optimization (PSO) method to minimise costs, whereas reference [16] utilised group search optimization (GSO) to maximise reliability. However, none of the previous studies have specifically focused on the multi-objective optimization problem for component capacity in MMG system, considering trade-offs between reliability, overall cost, and dump load size. Moreover, the impact of data uncertainties on MMG resilience [22] has received limited attention, hindering the development of robust and adaptable systems.

This study addresses the limitations of prior research by proposing a multi-objective optimization approach for optimizing residential MMG design and operation. This approach tackles the interplay between achieving reliability, minimizing cost, and reducing dump load size, all crucial factors for efficient MMG operation. By employing the Iterative Pareto Fuzzy (IPF) technique, this approach allows for simultaneous optimization of these competing objectives, providing a comprehensive understanding of the trade-offs involved. This focus on multi-objective optimization and data uncertainties aligns with the growing emphasis on smart grid development, which prioritizes the integration of renewable energy sources while ensuring grid stability and efficiency [23,24]. Furthermore, we investigate the impact of data uncertainties on residential MMG resilience by introducing Gaussian and Weibull noise models to simulate variations in solar irradiance and wind speed data.

The remainder of this paper is arranged as follows: Section 2 presents the problem formulation and provides a detailed description of the proposed IPF technique. Section 3 includes simulation results, as well as analysis and evaluations. Finally, Section 4 presents the conclusion.

2. Problem Formulation and Methodology

This section presents the research methodology, including data collection on wind speed and solar irradiance. It details the components of the residential MMG system, comprising photovoltaic (PV) panels, wind turbines (WT), ESS, and electrical loads, as illustrated in Fig. 1.

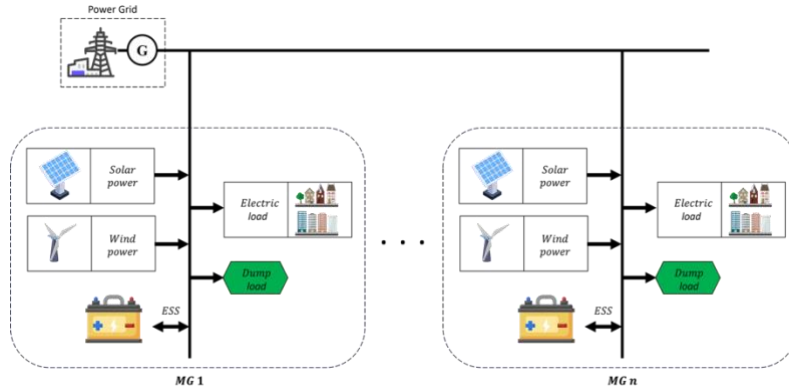


Fig. 1 Residential multi-microgrid system architecture

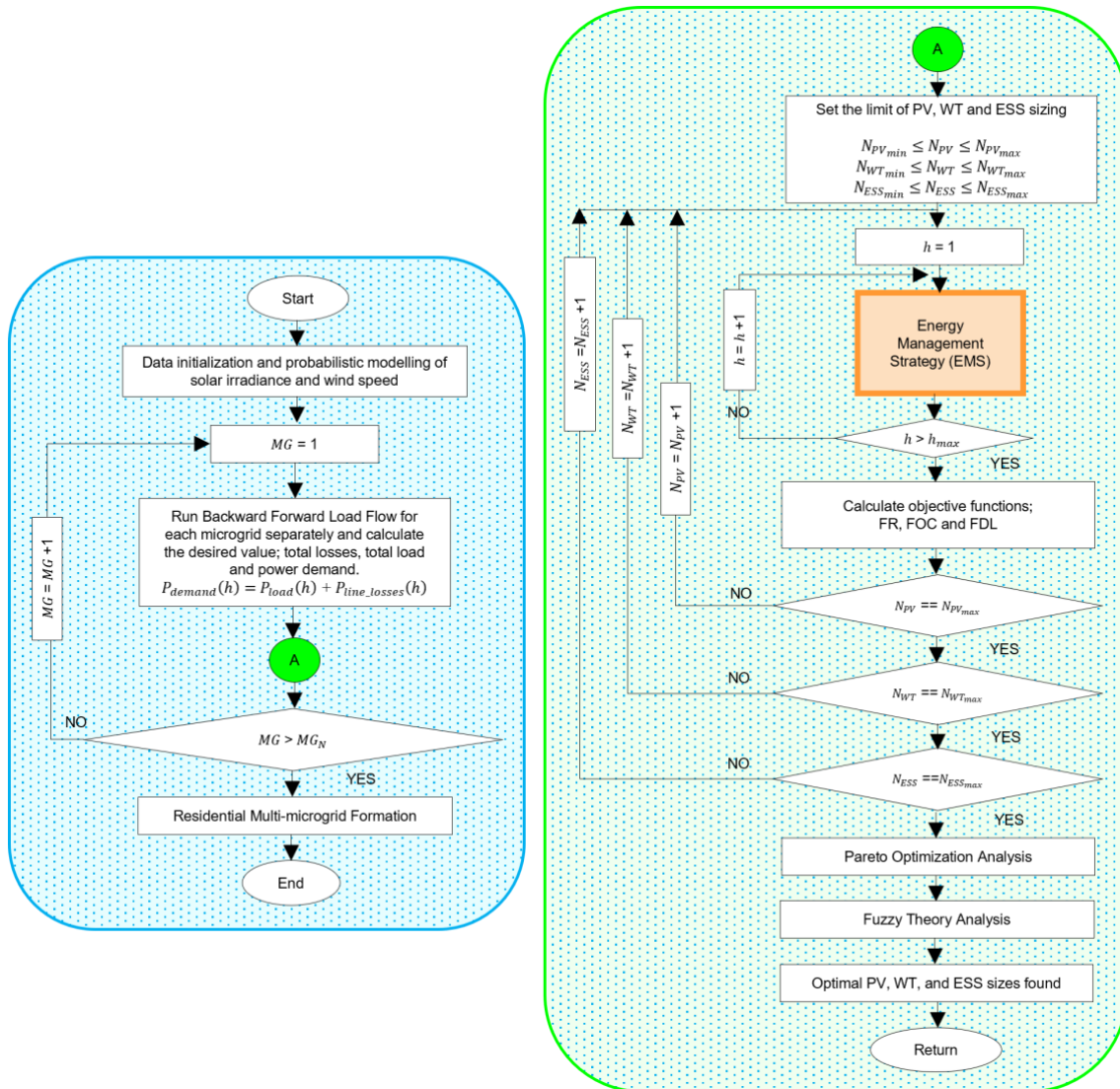


Fig. 2 Proposed residential multi-microgrid construction process

The capacity optimization method is also described, employing the IPF technique with objective functions that evaluate reliability, overall cost, and dump load size. Finally, the performance of the residential MMG system is evaluated using the self-sufficiency index (SSI). The overall process of

proposed residential MMG construction is illustrated in Fig. 2.

2.1. Solar Irradiance and Wind Speed

The simulation uses solar irradiance and wind speed data obtained from the NASA POWER database for Mersing City, southern Malaysia (2.5752° N, 103.8119° E). The data is in hourly resolution and is visualized in Fig. 3. The selected daily solar irradiance and wind speed data for hours 1 to 24 are shown in Fig. 4 and Fig. 5, respectively.

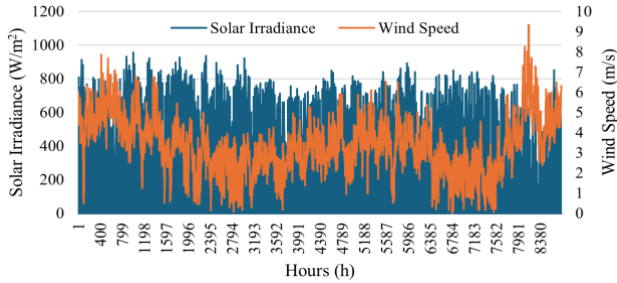


Fig. 3 Annual solar irradiance and wind speed data

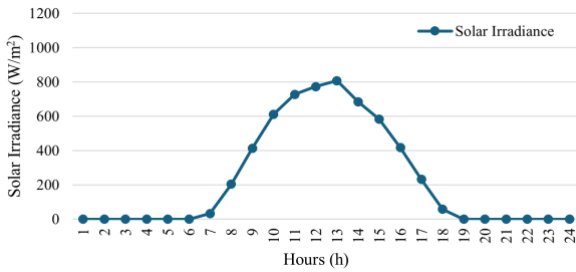


Fig. 4 Daily solar irradiance data

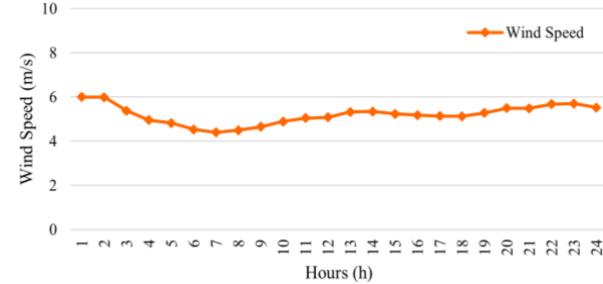


Fig. 5 Daily wind speed data

This study modeled solar irradiance data using normal probability density functions (PDFs) [25] and wind speed data using Weibull PDFs [26,27]. Uncertainty data was generated from the modeled PDFs by incorporating Gaussian-noise for the normal PDF [28] and Weibull-noise for the Weibull PDF [29]. The uncertainty in solar irradiance data followed a normal distribution $N(\mu, \sigma)$, with μ representing the mean and σ representing the standard deviation. The uncertainty in wind speed data, on the other hand, was characterized by the scale (c) and shape (k) parameters of the Weibull distribution, denoted as $W(c,k)$.

2.2. System Components Modeling

2.2.1. Photovoltaic system modeling

This research utilizes a simplified model for PV power output, considering both solar irradiance and the area of the PV panels. Equation (1) [30-33] describes the output power

of a photovoltaic system at time h , where $P_{PVout}(h)$ represents the PV output power, G represents the solar irradiance, N_{PV} represents the effective area of the PV panels, and η_{PV} represents the efficiency of the PV panels.

$$P_{PVout}(h) = G \times N_{PV} \times \eta_{PV} \quad (1)$$

The product of G and N_{PV} essentially captures the total solar energy received by the PV system. This captured energy is then converted into electrical power by the panels with an efficiency of η_{PV} , resulting in the final PV output power of the system at time h .

2.2.2. Wind turbine system modeling

The equation (2) [34,35] describes the output power of a wind turbine at time h , where $P_{WTout}(h)$ represents the wind turbine output power. The expression is defined over different wind speed ranges: for wind speeds below the cut-in wind speed V_{ci} the turbine produces no power; between V_{ci} and the rated wind speed V_r , the power output follows a cubic relationship with wind speed, incorporating parameters α and b , and is limited by the rated power P_r ; for wind speeds between V_r and the cut-out wind speed V_{co} , the output remains constant at the rated power; and for wind speeds exceeding V_{co} , the turbine again produces no power.

$$P_{WTout}(h) = \begin{cases} 0, & V < V_{ci} \\ \alpha \times V^3 - b \times P_r, & V_{ci} \leq V \leq V_r \\ P_r, & V_r \leq V \leq V_{co} \\ 0, & V > V_{co} \end{cases} \quad (2)$$

$$\alpha = \frac{P_r}{V_r^3 - V_{ci}^3}$$

$$b = \frac{V_{ci}^3}{V_r^3 - V_{ci}^3}$$

2.2.3. Energy storage system modeling

The inequality in equation (3) describes the state of charge (SoC) constraint for an ESS, where ESS_{SoC} (kWh) represents the current SoC of the energy storage system, ESS_{minSoC} denotes the minimum allowable SoC, and ESS_{maxSoC} signifies the maximum allowable SoC [36].

$$ESS_{minSoC} \leq ESS_{SoC} \leq ESS_{maxSoC} \quad (3)$$

Equation (4) represents a constraint on the charging or discharging rate of an ESS, where ESS_{chg_dischg} (kW) denotes the current charging or discharging rate of the ESS, and $ESS_{Limit_chg_dischg}$ signifies the maximum allowable charging or discharging rate.

$$ESS_{chg_dischg} \leq ESS_{Limit_chg_dischg} \quad (4)$$

These constraints ensure that the ESS operates within specified limits [37], maintaining both its SoC within a safe range to prevent overcharging or over discharging, and its charging or discharging rate within a defined limit to uphold system stability and prevent damage to its components.

2.2.4. Load configuration modeling

The load profile of the residential MMG system, based on the IEEE-33 test system, is generated by combining demands from each bus within individual microgrids using equations (5) and (6).

$$L_{daily_{bus}} = \sum_{i=1}^I L_{bus_{demand}}(i) \times L_{norm} \quad (5)$$

$$L_{norm} = \sum_{h=1}^H L_{daily_{pattern}}(h) \div L_{max} \quad (6)$$

These demands are then adjusted to incorporate time variations outlined in the daily residential load patterns [38] and to adhere to the maximum load capacity of the test system. The load profiles of each microgrid utilized in this study are illustrated in Fig. 6.

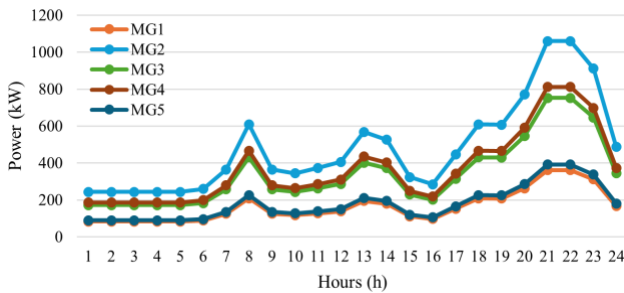


Fig. 6 Daily load profile of each microgrid

2.3. Sizing Optimization Method

2.3.1. Iterative pareto fuzzy technique

Complex design considerations, including reliability, overall cost, and dump load size, are addressed by an IPF optimization approach [38]. The method iteratively adjusts PV, WT, and ESS sizes within specified ranges (Equations 7-9). Data utilised for capacity optimization is summarised in Table 1 to Table 3.

$$N_{PV_{min}} \leq N_{PV} \leq N_{PV_{max}} \quad (7)$$

$$N_{WT_{min}} \leq N_{WT} \leq N_{WT_{max}} \quad (8)$$

$$N_{ESS_{min}} \leq N_{ESS} \leq N_{ESS_{max}} \quad (9)$$

Table 1. PV and WT parameters

PV and WT parameters	Value	Units
Efficiency of PV, η_{PV}	16	%
Per unit area of PV array, N_{PV}	625	m ²
Min area of PV array, $N_{PV_{min}}$	625	m ²
Max area of PV array, $N_{PV_{max}}$	18,750	m ²
WT efficiency, η_{WT}	50	%
Per unit rated power of WT, N_{WT}	4	kW
Min power of WT, $N_{WT_{min}}$	4	kW
Max power of WT, $N_{WT_{max}}$	40	kW
Cut-in wind speed, V_{ci}	2.0	m/s
Rated wind speed, V_r	8.0	m/s
Cut-out wind speed, V_{co}	20.0	m/s

Table 2. ESS parameters

ESS parameter	Value	Units
Per unit rated power of ESS, N_{ESS}	500	kWh
Min power of ESS, $N_{ESS_{min}}$	500	kWh
Max power of ESS, $N_{ESS_{max}}$	15000	kWh
Hourly charging/discharging limit, $ESS_{Limit \ chg \ dischg}$	50% of rated power ESS	
Min and max SoC of ESS, ESS_{SoC}	30% and 80% of rated capacity ESS	

Table 3. Economic and planning parameters

Economic planning parameters	Value	Units
Average inflation rate, β	9	%
Average interest rate, γ	12	%
Average escalation rate, v	12	%
Life span of the project, L_h	20	years
Life span of the PV, L_{PV}	20	years
Life span of the WT, L_{WT}	20	years
Life span of the battery, L_{ESS}	10	years
Initial cost of PV, α_{PV}	450	\$/m ²
Initial cost of WT, α_{WT}	100	\$/m ²
Initial cost of ESS, α_{ESS}	100	\$/kWh
Annual OM cost of PV, $\alpha_{OM_{PV}}$	4.3	\$/m ² /year
Annual OM cost of WT, $\alpha_{OM_{WT}}$	2.5	\$/m ² /year
Annual OM cost of ESS, $\alpha_{OM_{ESS}}$	10	\$/kWh/year
Salvage value of PV, α_{SPV}	45	\$/m ²
Salvage value of WT, α_{SWT}	10	\$/m ²
Additional WT cost per unit, $Cost_{WTadd}$	10 % of WT total cost	
Analysis duration	8760	hours

2.3.2. Energy management strategies

This section presents a rule-based EMS for microgrid capacity planning as shown in Table 4.

Table 4. Operational states of rule-based EMS

State	Rule (IF)
1	$P_{gen} > P_{demand}$
2	$P_{gen} > P_{demand} \ \& \ ESS_{SoC}(t-1) < ESS_{maxSoC}$
3	$P_{gen} > P_{demand} \ \& \ ESS_{SoC}(t-1) \geq ESS_{maxSoC}$
4	$P_{gen} < P_{demand} \ \& \ ESS_{SoC}(t-1) > ESS_{minSoC}$
5	$P_{gen} < P_{demand} \ \& \ ESS_{SoC}(t-1) \leq ESS_{minSoC}$

The focus is on ensuring microgrid functionality during islanding events, where the system operates independently. Rule-based EMS defines five operational states, each with specific control rules tailored to optimize microgrid functionality.

State 1 ensures a balance between power generation and demand, promoting stable power supply. State 2 prioritizes charging ESS to enhance resilience by storing surplus power. State 3 manages unutilized surplus power to dump load. State 4 involves discharging the ESS to maintain continuous power supply during excess demand. State 5 addresses significant deficits, facilitating informed decision-making to mitigate disruptions.

2.3.3. Objective functions

2.3.3.1. Reliability function

Energy efficiency and reliability in meeting load demand can be assessed using the energy index of reliability (EIR). Optimal microgrid system capacity requires an EIR over 0.85 for 85% reliability [39]. The following formulas calculate EIR.

$$EIR (FR) = 1 - \frac{P_{notsupp}}{P_{demand}} \quad (10)$$

$$P_{notsupp} = \sum_{h=1}^H \left[P_{demand}(h) - \left(\begin{array}{c} P_{gen}(h) \\ + P_{ESS_{SoC}}(h) \\ - P_{ESS_{minSoC}}(h) \end{array} \right) \right] \times U(h) \quad (11)$$

Equation (11) calculates $P_{notsupp}$ (power not supplied) for 8760 hours per year. If the energy surplus is more than the generated power, the step function $U(h)$ is zero, otherwise it is one. Power surplus and deficit are determined by imbalance power evaluation. The main indicators for assessing imbalance power are generated power (P_{gen}) and demand power (P_{demand}).

Reliability assessments may overestimate generating power and misjudge the dependability of microgrid if total line losses are not considered. This study calculates microgrid line losses using Backward Forward Load Flow (14) with a voltage limit constraint (15).

$$P_{gen}(h) = P_{PVout}(h) + P_{WTout}(h) \quad (12)$$

$$P_{demand}(h) = P_{load}(h) + P_{line_losses}(h) \quad (13)$$

$$P_{line_losses}(h) = |V_{i,h}| |V_{j,h}| |Y_{ij}| \cos \left(\begin{array}{c} \theta_{ij} \\ -\delta_{i,h} \\ -\delta_{j,h} \end{array} \right) \quad (14)$$

$$V_{min} \leq V_{i,h} \leq V_{max}, i \neq l, V_{i,h} = l \angle 0 \quad (15)$$

2.3.3.2. Overall cost function

The overall cost (*Overall Cost*) in equation (16) is calculated by summing the initial investments (I_i) and subtracting the annual operation and maintenance costs (OM_i), as well as the salvage values (S_i) for PV, WT, and ESS.

$$Overall \ Cost \ (FOC) = \sum_{i=P.V., \ WT, \ ESS} I_i - OM_i - S_i [X(h) \times Cost_{WTadd}] \quad (16)$$

$$X(h) = N_{WT} - l \quad (17)$$

These components are influenced by various factors detailed in Equations (18) through (25), such as the number of WT (N_{WT}), PV panels (N_{PV}), and ESS (N_{ESS}), as well as parameters like α_{PV} , α_{WT} , α_{ESS} , α_{OMPV} , α_{OMWT} , α_{OMESS} , α_{SPV} , and α_{SWT} . The additional cost of WT ($Cost_{WTadd}$) is factored in at each time interval (h) and the salvage value of the ESS is not considered in this study. These calculations contribute to assessing the overall cost of the system over time.

$$I_{PV} = \alpha_{PV} N_{PV} \quad (18)$$

$$I_{WT} = \alpha_{WT} A_{WT} N_{WT} \quad (19)$$

$$I_{ESS} = \alpha_{ESS} \times P_{ESS} \times N_{ESS} \times \sum_{i=1}^{Y_{ESS}} \left(\frac{1+\gamma}{1+\beta} \right)^{(i-1)L_h} \quad (20)$$

$$OM_{PV} = \alpha_{OMPV} \times N_{PV} \times \sum_{i=1}^{L_h} \left(\frac{1+\gamma}{1+\beta} \right)^i \quad (21)$$

$$OM_{WT} = \alpha_{OMWT} \times A_{WT} \times N_{WT} \times \sum_{i=1}^{L_h} \left(\frac{1+\gamma}{1+\beta} \right)^i \quad (22)$$

$$OM_{ESS} = \alpha_{OMESS} \times P_{ESS} \times N_{ESS} \times \sum_{i=1}^{L_h} \left(\frac{1+\gamma}{1+\beta} \right)^i \quad (23)$$

$$S_{PV} = \alpha_{SPV} \times N_{PV} \times \left(\frac{1+\beta}{1+\gamma} \right)^{L_h} \quad (24)$$

$$S_{WT} = \alpha_{S_{WT}} \times A_{WT} \times N_{WT} \times \left(\frac{I + \beta}{I + \gamma} \right)^{Lh} \quad (25)$$

2.3.3.3. Dump load size function

The P_{dump} equation in (26) calculates surplus power beyond the storage capacity of the system or demand. This unutilized surplus power is redirected to the dump load, ensuring efficient energy management, and preventing wastage.

$$P_{dump}(FDL) = \sum_{h=1}^H P_{surplus} - [P_{ESS} - ESS_{SoC}(h-1)] \quad (26)$$

2.4. Performance Evaluation by Self-sufficiency Index

The SSI assesses the autonomy of the microgrid by evaluating its ability to independently meet demands. It is derived using Equation (27), dividing the total power

generated by the microgrid by the total power consumed, including demand and dump load, and expressed as a percentage.

$$SSI = \frac{\text{Total power generated}}{\text{Total power consumption}} \times 100\% \quad (27)$$

where

$$\text{Total power generated} = \sum_{h=1}^H P_{gen}(h) \quad (28)$$

$$\text{Total power consumption} = \sum_{h=1}^H P_{demand}(h) + P_{dump}(h) \quad (29)$$

This metric categorizes microgrid performance: a higher SSI (above 80%) indicates strong autonomy, a moderate SSI (between 50% and 80%) suggests reasonable autonomy, and a lower SSI (below 50%) reveals limited resources and dependency on the main grid. The rule-based EMS employed in this study is illustrated in Fig. 7.

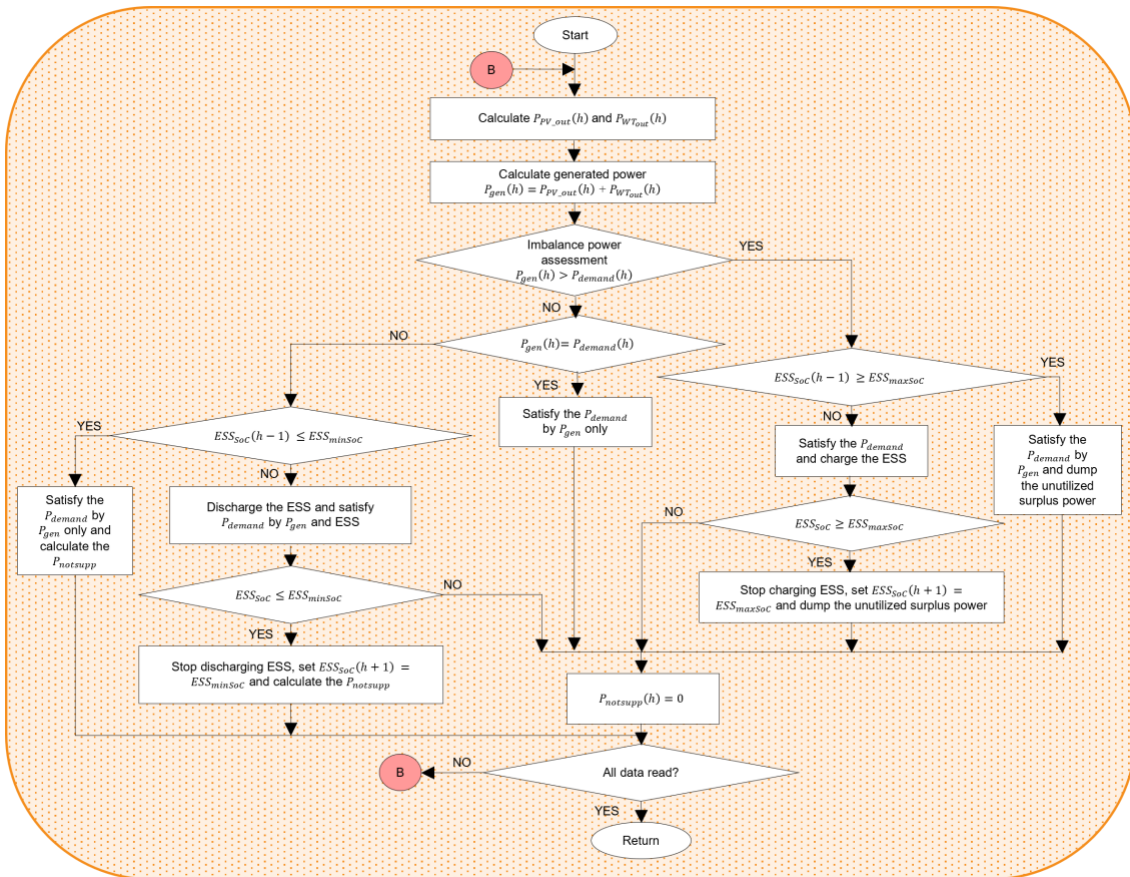


Fig. 7 Proposed rule-based energy management strategy

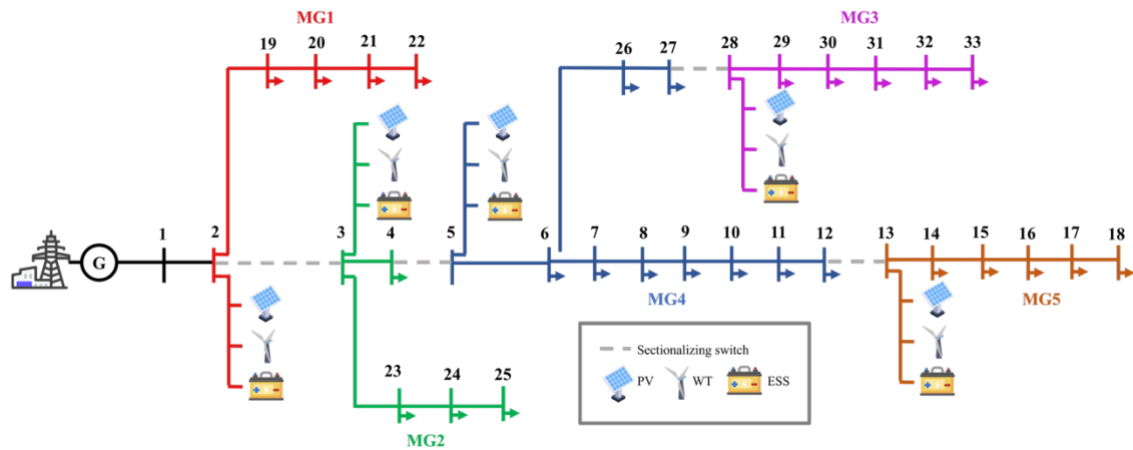


Fig. 8 Modified IEEE 33 bus system with autonomous microgrids

3. Results and Discussion

The method proposed in this study is evaluated using the IEEE 33-bus test system, which operates at a nominal voltage of 12.66 kV and has a peak load of 3715 kW. MATLAB software is employed for analysis. To adapt the test system for our purposes, we have customized it to accommodate five autonomous MGs. RES and ESS are strategically positioned at the first bus of each MG, as depicted in Fig. 8. The optimal sizing of RES and ESS is determined through the assessment of a multi-objective problem utilizing the IPF technique.

3.1. Performance Evaluation by Self-sufficiency Index

An analysis of Fig. 9 and Fig. 10, exploring the optimal sizing of RESs and ESS units across microgrids, reveals their respective capacities.

PV unit numbers vary, with MG 2 boasting the highest count at 23 units, suggesting a significant emphasis on solar power generation. The uniform presence of a single wind turbine unit in each microgrid underscores its role as a supplementary energy source. Meanwhile, ESS unit numbers differ, with MG 2 featuring the highest count at 21 units.

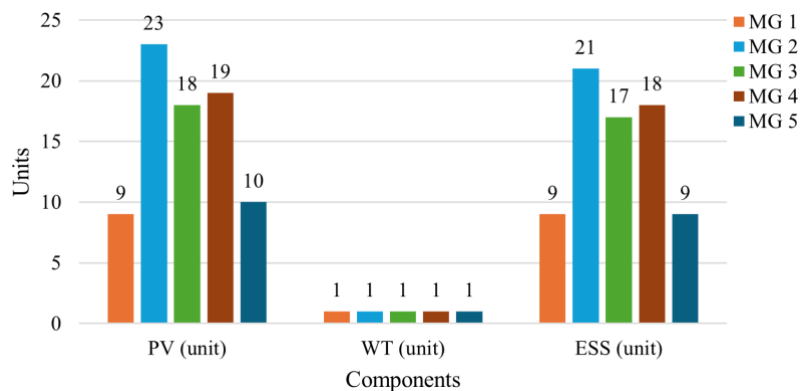


Fig. 9 Optimal sizing unit of PV, WT and ESS for each microgrid

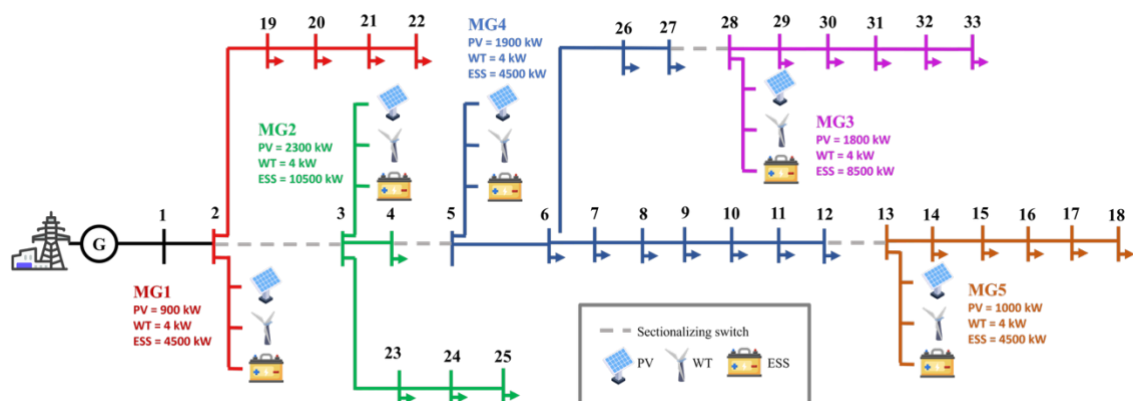


Fig. 10 Modified IEEE 33 bus system with integration of optimal PV, WT and ESS capacity

In a detailed examination of the microgrid data shown in Fig. 11 to Fig. 13, each system's performance is assessed across multiple key parameters.

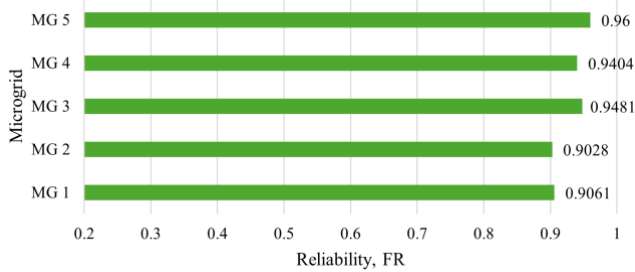


Fig. 11 Reliability function values for each microgrid

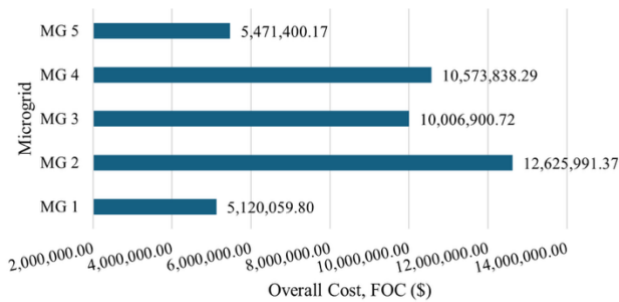


Fig. 12 Overall cost function values for each microgrid

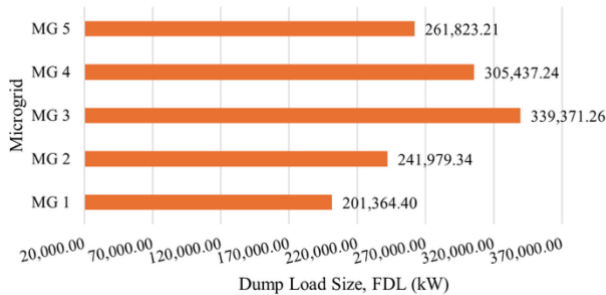


Fig. 13 Dump load size function values for each microgrid

The reliability function values, indicative of the microgrid's dependability, vary among the microgrids with MG 3 leading at 0.9481. However, the overall cost function unveils a trade-off, as MG 2, with the highest cost of \$12,625,991.37, contrasts with MG 1 and MG 5, which showcase more cost-effective designs. The dump load size function provides further insights, with MG 3 displaying the largest dump load size.

3.2. Energy Management Analysis

Fig. 14 to Fig. 18 demonstrate the operational output of the rule-based EMS for each microgrid. These visualisations utilise the optimal sizing results obtained earlier, demonstrating how the system utilizes resources to meet demands. Each picture illustrates the power generation and

consumption pattern, as well as the ESS profile, for the corresponding microgrid.

The microgrids exhibit differences in their minimum and maximum values for both total generation and demand power. These variations primarily originate from the differing numbers of buses within each microgrid area. The microgrid with the highest SSI will be examined to understand these power profiles.

Notably, MG5 stands out with SSI of 96.52 percent, surpassing the other MGs. On the other hand, MG2 in Fig. 15 shows SSI with the lowest value of 90.71 percent.

During hours 1 to 5 in MG5 shown in Fig. 18, the generation power is lower than the demand power resulting in ESS discharging (State 4). Generation power surpassed the demand power in hours 9 to 11 allowing ESS charging (State 2) and leading to incline in SoC from 65.19 percent to 82.16 percent.

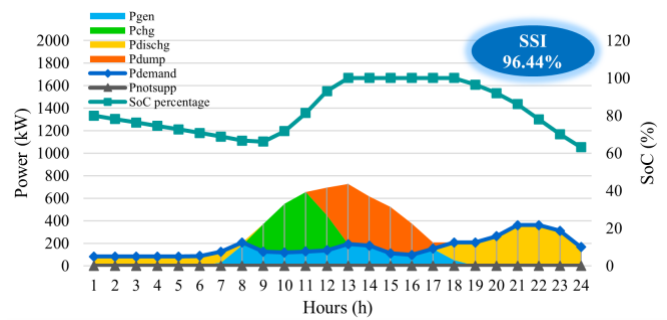


Fig. 14 MG1 power generation and consumption profile

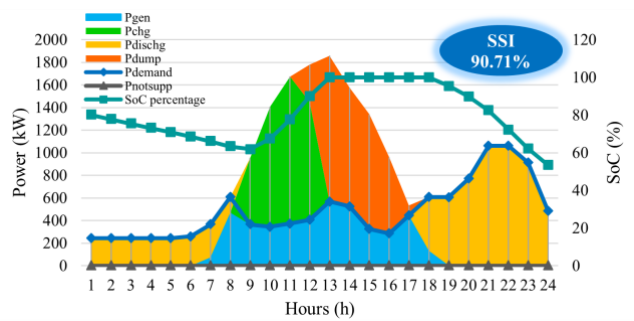


Fig. 15 MG2 power generation and consumption profile

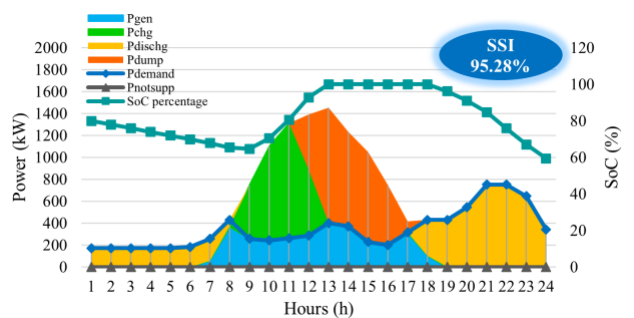


Fig. 16 MG3 power generation and consumption profile

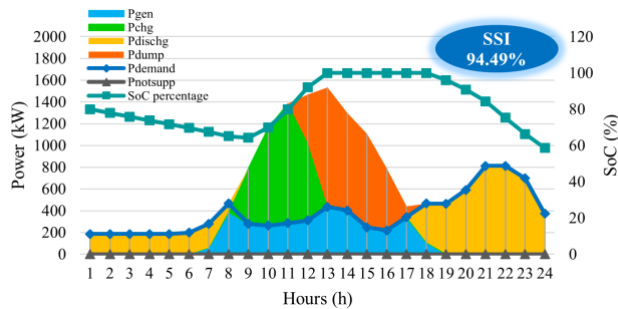


Fig. 17 MG4 power generation and consumption profile

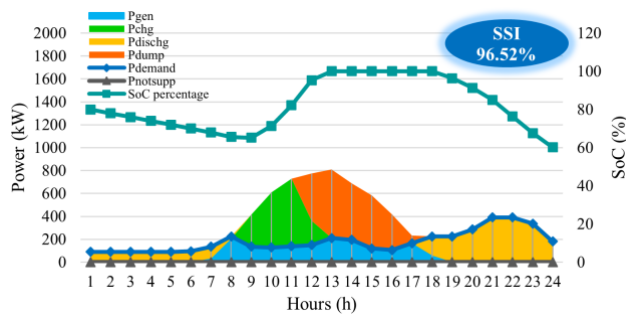


Fig. 18 MG5 power generation and consumption profile

Due to excess generation power exceeding the demand power, the dump load is activated in hour 12 (State 3). In hours 13 to 17, high generation power was sustained, results in continued utilization of the dump load (State 3). Finally, hours 18 to 24 show a gradual decline in generation power indicating increased ESS reliance to meet the power demand (State 4). The upward and downward profile of SoC shows the charging and discharging behaviour of ESS, respectively.

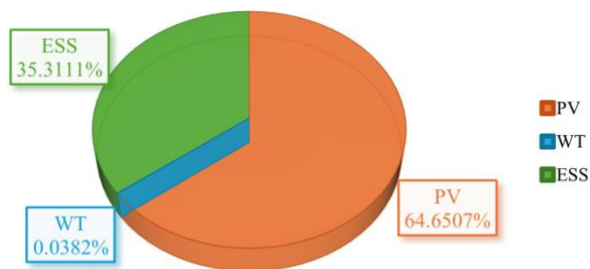


Fig. 19 Energy contribution in residential MMG system

The energy contribution in the residential MMG system visualized in Fig. 19 is characterized by a predominant reliance on PV sources, constituting 64.6507% of the total energy contribution. This highlights a significant emphasis on solar power as the primary means of electricity generation in the proposed residential MMG. Conversely, wind turbine energy contributes a minimal 0.0382%, indicating that wind power plays a comparatively minor role in the overall energy composition. An ESS is responsible for a significant amount (35.3111%), suggesting that energy storage and management are strategically prioritized for improved residential MMG

flexibility and stability. To summarize, the residential MMG system demonstrates a strong integration of solar energy as the primary source, supported by an effective ESS, with wind power playing a minor role in the overall energy generation. The precise composition of this energy combination is based on patterns of energy consumption and environmental conditions.

3.3. Robustness Analysis

This study investigates the impact of distribution noise on the autonomy performance of microgrids considering the uncertainties associated with solar irradiance and wind speed data. The distribution noise is introduced across a range of values from -0.15 to 0.15. Two distinct conditions are considered: an overestimated noise level characterized by positive value parameters, and an underestimated noise level represented by negative value parameters. These conditions allow for a thorough examination of how varying degrees of noise affect the resilience and autonomy of microgrid systems. The analysis is conducted using a residential MMG system configuration that has been optimized using the IPF technique.

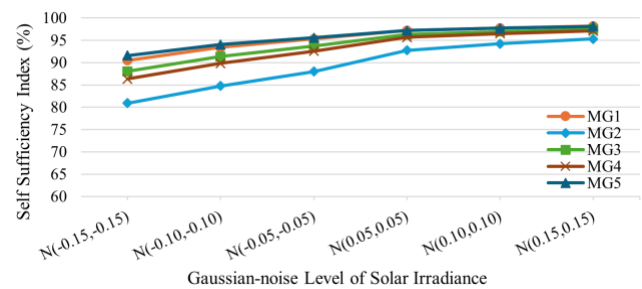


Fig. 20 Impact of uncertainty solar irradiance on self-sufficiency index for each microgrid

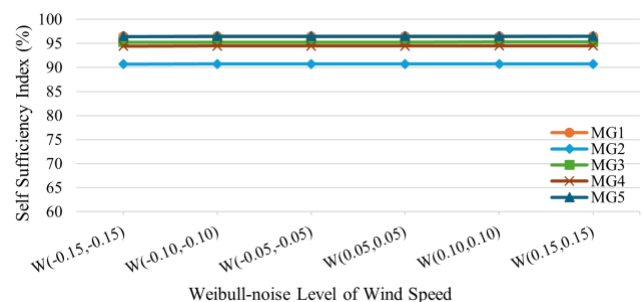


Fig. 21 Impact of uncertainty wind speed on self-sufficiency index for each microgrid

Based on Fig. 20, the SSI values demonstrate a clear correlation with the level of Gaussian-noise introduced into solar irradiance data modeling. Under an overestimated Gaussian-noise level, SSI values are consistently higher, indicating improved microgrid resilience. For example, MG5 shows a significant increase in SSI values from 91.5579 at $N(-0.15, -0.15)$ to 98.1048 at $N(0.15, 0.15)$, demonstrating its resilient performance amidst uncertainty. Conversely, SSI values significantly decrease under underestimated noise

levels which highlights the unfavorable impact on microgrid resilience. At noise level -0.15, MG2 demonstrates the lowest SSI value among all microgrids.

The analysis of Weibull-noise introduced to wind speed data in Fig. 21 reveals some differences compared to the trends observed with Gaussian-noise in solar irradiance data. For instance, MG5 improves SSI values from 96.5021 at $W(-0.15, -0.15)$ to 96.5215 at $W(0.15, 0.15)$, however this change is relatively small compared to Gaussian noise. This shows that Weibull-noise may not affect microgrid resilience as much as Gaussian noise on solar irradiance data. The smaller differences in SSI values between noise levels suggest that microgrid resilience to wind speed variability is less sensitive than to solar irradiance variability, possibly due to the relatively small energy contribution of wind turbines to the microgrid system. Overall, the findings suggest that while microgrid resilience remains robust against data uncertainty, its sensitivity varies according to the type of noise and the energy contributions of its components.

4. Conclusion

The optimization of residential MMG system using the IPF technique with incorporation of EMS, prioritizing a balance between reliability, cost, and dump load size, yielded valuable insights into their effective design and operation under uncertainties. The results confirmed that PV emerges as the dominant energy source, necessitating effective energy storage integration (35.3111%) to enhance resilience and self-sufficiency. Wind turbines, while contributing minimally (0.0382%), can still play a supplementary role in diversifying the energy mix. The analysis, based on modifications to the IEEE 33-bus test system with five autonomous microgrids, revealed key trade-offs: MG 3 achieved the highest reliability (0.9481) but at the highest cost (\$12,625,991.37), while MG 1 and MG 5 offered more cost-effective designs. Robustness analysis using Gaussian and Weibull noise models on optimal residential MMG system further demonstrated the resilience of the proposed approach to data uncertainty, with an SSI exceeding 80%. These findings underscore the importance of concurrently addressing trade-offs between multiple objectives and uncertainties in the design and operation of residential MMGs, offering valuable insights for enhancing energy autonomy and resilience. Future research could explore advanced uncertainty mitigation techniques through the development of robust forecasting models for solar irradiance and wind speed data. Additionally, investigating the integration of emerging technologies, such as hydrogen storage or tidal power, can diversify the energy mix and enhance microgrid flexibility. By pursuing these avenues of research and development, the full potential of MMGs can be unlocked as key players in building resilient, sustainable, and distributed energy systems for the future.

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Author Contributions

All authors were responsible for the conceptualization, validation, resources, data curation, software development, and project administration. They jointly contributed to the methodology, formal analysis, investigation, original draft preparation, review and editing, visualization, supervision, and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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